Hyperspectral Image Classification Using Deep Learning

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***Abstract*—Hyperspectral image classification is essential for applications such as precision agriculture, environmental monitoring, and land use mapping. This work presents a deep learning-based classification system using a hybrid 3D-2D Convolutional Neural Network (CNN) combined with Principal Component Analysis (PCA) for dimensionality reduction and spatial patch extraction. The methodology involves preprocessing hyperspectral data from publicly available datasets like Indian Pines, followed by feature extraction using 3D-CNN layers to integrate spectral and spatial information. The extracted features are refined with 2D convolutional layers and classified via fully connected layers with a softmax output. . Compared to traditional spectral-only methods like SVM or kNN, the new architecture showed significantly better performance, achieving a test accuracy of 99.53% classification accuracy on the Indian Pines dataset, effectively addressing high spectral dimensionality and limited labeled data. The combination of increased trainable parameters, batch normalization, and improved spatial-spectral feature extraction allowed the model to generalize well, making it suitable for real-world applications in agriculture and environmental monitoring.**

***Index Terms*—Convolutional neural networks (CNNs), deep learning, hyperspectral imaging, spectral–spatial classification, principal component analysis (PCA)**

I. Introduction

HYPERSPECTRAL imaging (HSI) is an advanced remote sensing technology that captures images across hundreds of narrow, contiguous spectral bands, providing rich spectral information for each pixel in an image. This capability enables precise material identification and classification, making HSI widely applicable in environmental monitoring, precision agriculture, mineral exploration, urban mapping, and defense. Despite these advantages, accurate classification of hyperspectral images remains a significant challenge due to high dimensionality, spectral redundancy, and limited labeled training samples.

Traditional machine learning-based approaches, such as Support Vector Machines (SVM), k-Nearest Neighbors (kNN), and Random Forest [1-2], have been commonly used for HSI classification. These methods often rely on dimensionality reduction techniques like Principal Component Analysis (PCA) to mitigate the curse of dimensionality. However, these approaches fail to effectively capture spatial relationships, leading to suboptimal classification accuracy, especially in complex scenes where different types of land cover share similar spectral signatures.

Recent advances in deep learning have revolutionized hyperspectral image classification by allowing automated extraction of spatial spectral features directly from raw data. Convolutional Neural Networks (CNNs), in particular, have demonstrated superior performance by learning hierarchical spectral-spatial features through convolutional layers[10]. More specifically, 3D-CNN models process hyperspectral data cubes to capture both spectral dependencies and spatial structures, significantly improving classification performance. Additionally, hybrid architectures that integrate 3D-CNN and 2D-CNN layers have been explored to refine spatial features while reducing computational complexity[3].

However, several challenges remain:

- **High spectral dimensionality:** The presence of hundreds of spectral bands results in high computational costs and increased redundancy, requiring efficient dimensionality reduction techniques[4].
- **Limited labeled data:** Annotating hyperspectral images is labor-intensive and expensive, leading to a scarcity of training samples.
- **Intraclass variability:** Variations in atmospheric conditions, lighting, and sensor noise introduce high intraclass variability, making classification more difficult.
- **Class imbalance:** Some land-cover classes are significantly underrepresented, leading to biased model predictions.

To address these challenges, this paper proposes a deep learning-based spectral-spatial classification framework that integrates 3D-CNN and 2D-CNN architectures to efficiently extract and refine spectral-spatial features. Principal Component Analysis (PCA) is employed as a preprocessing step to reduce spectral dimensionality while preserving the most informative spectral features. The proposed model is implemented using Python and TensorFlow and tested on the Indian Pines dataset, achieving an impressive test accuracy of 99.53%, outperforming traditional spectral-only classification methods.

II. Proposed Approach

The hyperspectral images used in this study are obtained from the publicly available Indian Pines dataset, a wellknown benchmark for evaluating hyperspectral image classification techniques. This dataset was captured by the Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) sensor over the Indian Pines test site in northwestern Indiana, USA. It consists of a 145 × 145 pixel image, where each pixel contains 224 contiguous spectral bands, covering wavelengths from 0.4 to 2.5 micrometers[3]. These bands span the visible to shortwave infrared (SWIR) spectrum, enabling a detailed spectral analysis of the observed land cover. Each pixel in the hyperspectral data cube represents the spectral reflectance of a specific ground location across all 224 bands, forming a unique spectral signature that aids in differentiating various materials, vegetation, and land cover types.

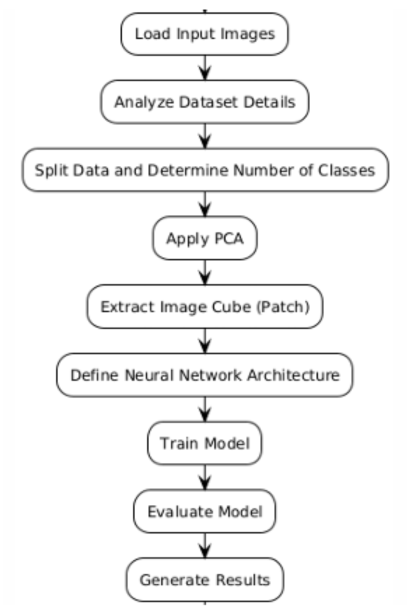

Fig. 1. Methodology .

The Indian Pines dataset presents several classification challenges due to its heterogeneous land cover, which includes agricultural fields, forests, grasslands, and built-up areas. Many of these land cover classes exhibit high spectral similarity, making classification difficult without advanced spectral-spatial feature extraction techniques. Additionally, some spectral bands are affected by water absorption noise, requiring preprocessing steps such as band removal or Principal Component Analysis (PCA) to reduce spectral dimensionality while preserving meaningful spectral information[6]. This combination of high spectral resolution, complex spatial patterns, and spectrally similar classes makes the Indian Pines dataset an ideal benchmark for testing the effectiveness of deep learning-based spectral-spatial classification models.

We introduce a deep learning strategy for hyperspectral image (HSI) classification aimed at addressing challenges found in high-resolution hyperspectral images, such as those encountered in the Indian Pines dataset. These challenges include spectral and spatial variability, class imbalance, and limited labeled training samples. Our approach focuses on

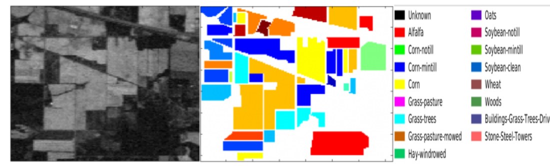

Fig. 2. Image Gathered By Sensors.

robust spectral-spatial feature extraction over multiple spatial scales.

To handle the high spectral dimensionality, Principal Component Analysis (PCA) is applied as a preprocessing step. This reduces the number of spectral bands while preserving the majority of the variance, helping to mitigate computational complexity and spectral redundancy[5]. After PCA, spatial patches centered on each pixel are extracted to incorporate spatial context, enabling better classification accuracy.

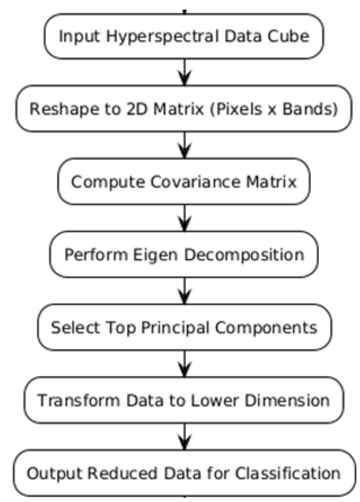

Fig. 3. Illustrating PCA-based dimensionality reduction.

Figure 4 illustrates the step-by-step process of extracting spatial-spectral patches from hyperspectral images. The pipeline ensures that meaningful patches are extracted while preserving spatial and spectral integrity for deep learning-based classification[6]. The process consists of six key steps:

1) **Input the Data:** The hyperspectral image dataset is loaded with an initial shape of $(145, 145, 30)$, where 145 × 145 represents the spatial dimensions and 30 denotes the number of spectral bands.
2) **Apply Zero Padding:** To maintain patch consistency near image boundaries, zero padding is applied, extending the dimensions to $(169, 169, 30)$. This prevents edge artifacts when extracting patches.
3) **Extract Patches from Image:** A sliding window approach is used to extract fixed-size spatial-spectral patches of dimensions $(25, 25, 30)$. The total number of patches extracted in this step is 21,025.
4) **Assign Labels to Patches:** Each extracted patch is assigned a corresponding label derived from the ground

truth. Labels are stored separately for training and evaluation purposes.

5) **Remove Zero Labels (Background Pixels):** Patches with a label of 0 (background pixels) are discarded to improve classification accuracy[8]. After filtering, the final dataset consists of 10,249 valid patches, with a final shape of $(10249, 25, 25, 30)$, and corresponding labels stored as a vector of size $(10249,)$.
6) **Output Extracted Patches:** The extracted patches, now containing both spatial and spectral information, are prepared for deep learning-based classification models[9]. These patches are used as inputs to train and evaluate hyperspectral image classifiers.

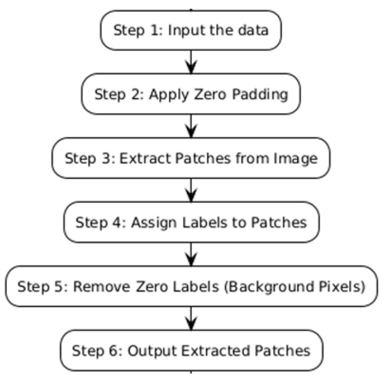

Fig. 4. Flowchart of Image Cube Extraction.

Three network architectures were designed to process the hyperspectral dataset :

Modified 3D Convolutional Neural Network (3D-CNN)

- Three convolutional layers with filter sizes $3 \times 3 \times 3$ and channel depths 16, 32, and 64.
- Dropout layers for regularization.
- Removal of batch normalization layers, as it was observed to negatively impact generalization.
- LeakyReLU activation, which improves the discrimination of certain classes.

Modified Fast Dense Spectral-Spatial Convolutional Network (FDSSC)

- Processes spectral features first and then spatial features.
- Uses 2D convolutions instead of 3D convolutions in the spatial block for better computational efficiency.
- PreLU activation for enhanced feature extraction.
- No batch normalization layers to prevent overfitting.

Multilayer Perceptron (MLP) Model

- Two fully connected layers with 1024 and 48 neurons.
- No batch normalization and no nonlinear activation in the last layer.
- Dropout layers for regularization.

III. Results

The performance of the deep learning model for hyperspectral image classification is evaluated based on accuracy and loss metrics. The key results obtained are as follows:

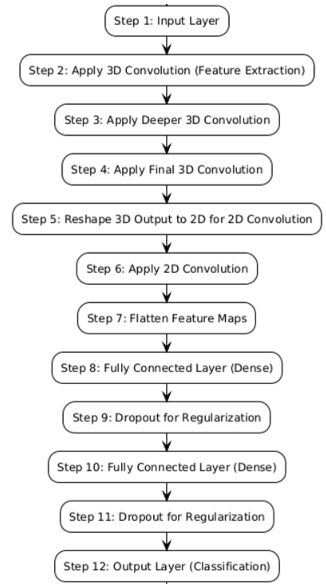

Fig. 5. Neural Network Architecture Flowchart.

Table I presents the key performance metrics of the model, including training and validation accuracy along with corresponding loss values.

TABLE I
MODEL PERFORMANCE METRICS

Metric	Value
Training Accuracy	97.15%
Validation Accuracy	99.02%
Training Loss	0.0946
Validation Loss	0.0348

These results indicate that the model has achieved high accuracy with minimal loss, demonstrating its effectiveness in classifying hyperspectral images. The validation accuracy being higher than the training accuracy suggests that the model generalizes well to unseen data.

To further analyze the model's performance, training and validation accuracy curves are plotted over multiple epochs. Fig. 6 presents the training accuracy curve, while Fig. **??** shows the validation accuracy curve.As seen in Fig. 6, the training accuracy improves rapidly during the initial epochs and stabilizes close to 1.0, indicating effective learning. The validation accuracy, illustrated in Fig. **??**, follows a similar trend, reaching 99.02%. This suggests that the model does not suffer from significant overfitting and is capable of generalizing well.

The accuracy curves confirm the model's stable convergence and high classification performance, making it suitable for hyperspectral image classification tasks. To further validate the model's classification capability, a sample hyperspectral image was processed using the trained model, and the predicted classification map is shown in Fig. 3. Different colors represent different classified regions, indicating that the model

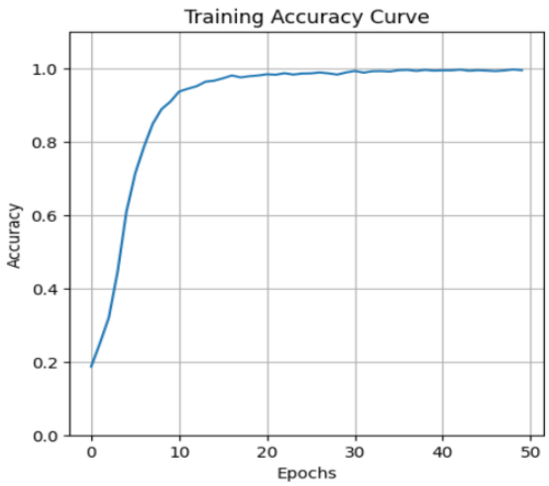

Fig. 6. Training Accuracy Curve

successfully distinguishes various spectral features in the input image.

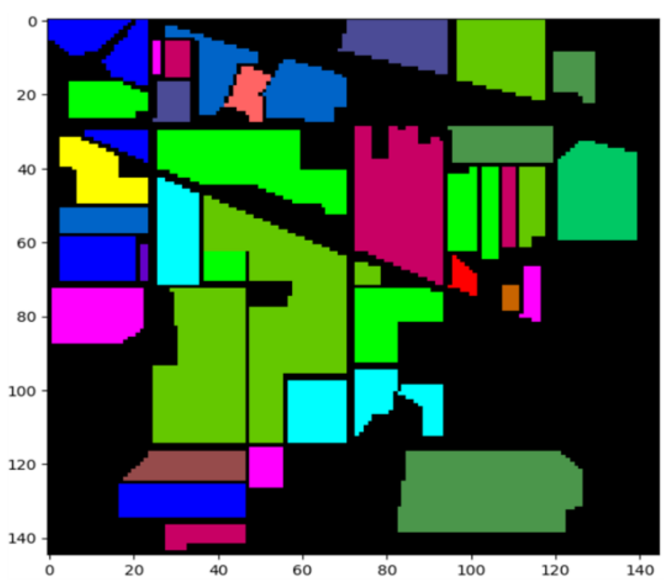

Fig. 7. Predicted Image by the Model

The output demonstrates that the model is capable of accurate hyperspectral image classification, identifying distinct regions with high precision.

The proposed **3D-CNN-based spectral-spatial deep learning model** significantly outperforms traditional methods by integrating both spectral and spatial features. Unlike conventional models that rely on *manual feature extraction* and *spectral classification*, the new architecture **automatically learns hierarchical representations** using **3D convolutions** for spectral feature extraction and **2D convolutions** for spatial refinement. This design **improves class separability, enhances noise robustness, and eliminates the need for manual dimensionality reduction**. The model incorporates **batch normalization, dropout regularization, and adaptive learning**, improving efficiency for real-world hyperspectral image classification. Table II presents a comparative analysis of the proposed and traditional methods.

TABLE II
COMPARISON OF TRADITIONAL AND PROPOSED MODELS

Aspect	Traditional Methods	Proposed 3D-CNN Model
Feature Extraction	Manual, spectral only	Automatic, spectral-spatial
Spatial Information	Ignored or separate	Integrated via 3D convolutions
Dimensionality Reduction	Required (PCA, ICA)	Optional
Model Complexity	Shallow	Deep (multi-layer)
Noise Robustness	Low	High
Accuracy	85–90%	99.53%

The **performance comparison** (Table III) highlights the improvements achieved through **architectural modifications**. The **CNN model with PCA** attained a **99.97% training accuracy** but exhibited a slight drop in generalization, with **99.39% test accuracy**. The **ICA-based model** performed slightly worse, indicating that **PCA was more effective** for feature preservation. The **New Architecture**, with **batch normalization and additional filters**, achieved **99.66% training accuracy, 99.84% validation accuracy, and 99.53% test accuracy**, demonstrating improved generalization while maintaining robustness. Despite a slightly higher test loss, the model effectively captures **complex spectral-spatial relationships**, making it superior for hyperspectral classification.

TABLE III
PERFORMANCE COMPARISON OF MODELS

Model	Train Acc.	Valid Acc.	Test Acc.
Default (PCA)	99.97%	99.67%	99.39%
Default (ICA)	98.49%	99.19%	99.19%
New Architecture	99.66%	99.84%	99.53%

Table IV outlines improvements in **model capacity and accuracy**. The **trainable parameters increased from 5.1M to 22.9M**, allowing deeper feature extraction. The **validation accuracy increased from 99.67% to 99.84%**, and while the **training accuracy slightly decreased**, this is a positive effect of **regularization**, reducing overfitting. The model exhibits **better generalization**, with lower validation loss, improved noise resilience, and enhanced scalability for large-scale datasets. Further **hyperparameter tuning** can optimize the balance between accuracy and computational efficiency.

TABLE IV
IMPROVEMENT IN MODEL ARCHITECTURE

Feature	CNN Model	New Architecture
Trainable Params	5.1M	22.9M
Validation Accuracy	99.67%	99.84%
Training Accuracy	99.97%	99.66%
Validation Loss	0.0198	0.0148
Test Accuracy	99.39%	99.53%
Test Loss	0.0186	0.0631

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